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A method for regional estimation of climate change exposure of coastal infrastructure: Case of USVI and the influence of digital elevation models on assessments

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Abstract

***Objective*:** This study tests the impacts of Digital Elevation Model (DEM) data on an exposure assessment methodology developed to quantify flooding of coastal infrastructure from storms and sea level rise on a regional scale. The approach is piloted on the United States Virgin Islands (USVI) for a one-hundred-year storm event in 2050 under the IPCC's 8.5 emission scenario (RCP 8,5). ***Method*:** Flooding of individual infrastructure was tested against three different digital elevation models using a GIS-based coastal infrastructure database created specifically for the project using aerial images. Inundation for extreme sea levels is based on dynamic simulations using Lisflood-ACC (LFP). ***Results*:** The model indicates transport and utility infrastructure in the USVI are considerably exposed to sea level rise and modeled storm impacts from climate change. Prediction of flood extent was improved with a neural network processed SRTM, versus publicly available SRTM (~30m) seamless C-band DEM but both SRTM based models underestimate flooding compared to LIDAR DEM. The modeled scenario, although conservative, showed significant flood exposure to a large number of access roads to facilities, 113/176 transportation related buildings, and 29/66 electric utility and water treatment buildings including six electric power transformers and six waste water treatment clarifiers. ***Conclusion*:** The method bridges a gap between large-scale non-specific flood assessments and single-facility detailed assessments and can be used to efficiently quantify and prioritize parcels and large structures in need of further assessment for regions that lack detailed data to assess climate exposure to sea level rise and flooding caused by waves. The method should prove particularly useful for assessment of Small Island Developing State regions that lack LIDAR data, such as the Caribbean.

1. Introduction

Hydrologic models of flooding are sensitive to vertical error and grid size of the underlying Digital Elevation Model (DEM) (Kenward, Lettenmaier et al. 2000, Vaze, Teng et al. 2010, Vousdoukas, Bouziotas et al. 2018) used in assessments. This work tests a coastal subset of Shuttle Radar Topography Mission (SRTM) elevation data against Light Detection and Ranging (LIDAR) data and a corrected SRTM in order to quantify errors in storm flood modeling assessments of coastal infrastructure that results from the DEMs. The methodology is developed and tested in the USVI, where coastal LIDAR data are available to empirically validate the DEMs and understand the challenges of using globally available data for national or regional scale assessment of critical coastal facilities. The high resolution and vertical accuracy of airborne LIDAR generated elevation data makes them an important asset for coastal planning as it leads to more detailed flood assessments with higher confidence (Gesch 2009, Cooper et al 2013, Runting et al. 2013, Zhu et al. 2015, Enwright et al 2017). DEMs are a major component of coastal flood predictions but lidar-derived DEMs are not available in all areas. Understanding the performance issues associated with the use of lower quality, widely available elevation data in flood models is therefore critical in climate change planning (Gesch 2018). This is particularly important as a uniform data standard is needed for planning at larger scales (e.g., regional) and/or in economically developing countries where high quality data are often not available and the impacts of large storms can be devastating.

Near global coverage DEMs, such as SRTM, the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and Global Digital Elevation Model (GDEM), offer globally-consistent scale and resolution and have been major assets in hydrologic and climate studies. Although, of these, SRTM offers the best vertical accuracy (Wang, Yang et al. 2012, Gesch 2018) at high horizontal resolution (30m), the data suffer from random noise, voids, striping and other errors that impact accuracy (Falorni, Teles et al. 2005, Hall, Falorni et al. 2005), with elevations generally biased high by several meters, particularly in densely vegetated or developed areas in high-relief terrain (Falorni, Teles et al. 2005, Sanders 2007, LaLonde, Shortridge et al. 2010, Shortridge and Messina 2011, Becek 2014) and causing considerable impacts on assessment of exposure to coastal flooding (Kulp and Strauss 2016). The appeal of the broad coverage and ease of availability of these data has led to many applications particularly at large spatial scales, see for example (Hinkel, Lincke et al. 2014, Neumann, Vafeidis et al. 2015, Vousdoukas, Voukouvalas et al. 2016, Vousdoukas, Mentaschi et al. 2018). At smaller spatial scales, such as the individual infrastructure facilities considered in the current work, the relative impact of DEM resolution and vertical errors on hydrologic models may be large but poorly understood. Lack of alternative, easily accessible and superior data sources, however, often necessitates use of SRTM data in applications that stretch the validity of results given the level of bias and error. When used in proper context (ex. larger geographic scale studies) however, accounting for limitations can make these data valuable assets for areas with limited data (Li and Wong 2010, Wang, Yang et al. 2012). Attempts to improve SRTM ex. (Baugh, Bates et al. 2013, Jarihani, Callow et al. 2015, Yamazaki, Ikeshima et al. 2017, Kulp and Strauss 2018) have been successful in addressing some of the issues inherent in these data, but the impact of refinements on smaller scale assessments when alternative data are not available are not usually considered in coastal exposure studies, adding to the uncertainty and unreliability of results (Gesch 2018).

1.1 Motivation – Coastal infrastructure is at risk, but difficult to assess risk at the regional scale

The Low Elevation Coastal Zone (LECZ) (less than 10 meters above sea level) contains 10% of global population but covers only 2% of the land area (McGranahan, Balk et al. 2007). Population in this zone is growing at faster rates than hinterland regions from in-migration (McGranahan, Balk et al. 2007, Smith 2011, Neumann, Vafeidis et al. 2015), particularly in economically developing countries. In light of sea level rise and potential increases in storm intensity, migration into the LECZ represents a movement towards risk. In the Caribbean, a majority of the airports, utilities and industrial infrastructure critical for economic development are located on the coast and relocation options are limited by lack of suitable land and costs associated with re-siting. The economic, social and political implications of this are just beginning to come to light and rest in part on the impacts climate change will have on such critical coastal infrastructure. In wealthier nations, climate change is emerging as a large component of planning in the coastal zone[1], accompanied by pledges for increased funding for resilience planning[2]. But even in wealthy nations, the scale of the problem means need will likely outstrip resources to deal with it (USGCRP 2017).

Resource-constrained nations face an even greater coastal climate threat, as they are experiencing in-migration to the LECZ at rates higher than the global mean (Neumann, Vafeidis et al. 2015) and have comparatively fewer resources to quantify, understand and plan for impacts (Smith 2011). This issue is particularly pertinent for Small Island Developing States (SIDS) in the Caribbean and elsewhere which contain the largest proportional share of their land area (16%) and amongst the highest population rates (13%) in the LECZ (McGranahan, Balk et al. 2007). The global scale of the risk to coastal infrastructure makes it highly unlikely that resource-constrained SIDS will be able to adapt at a pace adequate to match the threat, even with assistance from economically developed countries facing their own coastal climate change burden (Nurse, R.F. McLean et al. 2014, Cashman 2017). Methods are needed to support targeted and efficient

[1] https://www.nycedc.com/project/lower-manhattan-coastal-resiliency
[2] https://nymag.com/intelligencer/2019/03/bill-de-blasio-my-new-plan-to-climate-proof-lower-manhattan.html

planning and preparation for climate infrastructure adaptation in the resource constrained Caribbean and other SIDS regions. Individual facility level exposure and risk assessments (Monioudi, Asariotis et al. 2018) are one method of evaluation as an aid in planning, but detailed assessment methods such as this and others (Lichter and Felsenstein 2012, Taramelli, Valentini et al. 2015) require considerable data collection, and costs would be prohibitive given the total number of sites in need of evaluation at a regional scale. Other methods take national, regional, or single feature type (e.g., seaports) assessment approaches (Lam, Arenas et al. 2014, Chhetri, Corcoran et al. 2015, Kumar and Taylor 2015, Taramelli, Valentini et al. 2015, Kantamaneni 2016) targeted at evaluation of risk based on a host of factors including demographics, socioeconomic, and physical. Others have taken even larger scale approaches (Hinkel, Lincke et al. 2014, Rasmussen, Bittermann et al. 2018) important for framing the burden of climate change at the global scale. What is missing is a method that bridges the gap between costly single facility assessments and broad global or regional assessments not meant to target individual facilities (Duncan McIntosh and Becker 2017). Such a method should be efficient enough for application at a regional scale (e.g., the entire Caribbean), and accurate enough to quantify exposure at individual facilities, not as a means of offering facility level solutions, but an aim to prioritize and target future assessment work using more costly, localized, approaches. Data limitations are the largest barrier to progress in this area. The data challenge for flood assessment is universal, and many studies have relied on elevation data that may not be well examined for its appropriate use for a given methodology, even though impacts on estimates can be substantial (van de Sande, Lansen et al. 2012, Leon, Heuvelink et al. 2014, Gesch 2018). Solutions such as incorporating uncertainty into estimates have been developed but these present their own challenge of complexity in application, particularly at the preliminary assessment phase.

The remainder of this paper presents the data components required to efficiently quantify exposure to flooding from storms and sea level rise for critical coastal infrastructure at the individual facility level that is applicable on a regional scale. The method proceeds with identifying critical coastal facilities, creating geospatial data of those facilities, and then applying a dynamic storm model to determine exposure to flooding. Two DEMs – SRTM and a more recent derived product, CoastalDEM v1.1 (Kulp and Strauss 2018) are tested to assess their suitability for a regional level evaluation to be carried out in a subsequent phase of the research.

2. Data and Methods

The United States Virgin Islands (USVI) with high-quality coastal LIDAR data were used as the test site for method development. The USVI are Northern Islands of the Lesser Antilles chain, termed Leeward Islands, and straddle the North Atlantic Ocean and the Caribbean Sea. The islands consist of St. Croix, St. John and St. Thomas. As a territory of the United States, USVI has publicly-available coastal LIDAR DEMs, the standard against which the SRTM-based DEMs were tested for validation of the methodology for the region.

2.1 Data

Elevation data from NASA’s Shuttle Radar Topography Mission (SRTM) available from the United States Geological Survey’s EarthExplorer site (https://earthexplorer .usgs.gov) and Climate Central’s CoastalDEM (Kulp and Strauss 2018) are used in our exposure analyses. SRTM is freely available and provide near global coverage, but are of considerably lower resolution (1 arc second) and vertical accuracy than LIDAR data. CoastalDEM v1.1 is derived from SRTM, built using artificial neural networks to predict and correct the vertical errors, and contains substantially lower elevation bias and RMSE. Ground reference elevation data were not available so the airborne LIDAR DEMs (LIDAR) for the year 2013 were downloaded from NOAA Coastal Viewer (Office for Coastal Management) and used as ground truth. These data are distributed at 1m horizontal resolution (resampled to 10m for this analysis) with vertical and horizontal accuracy of 11 and 100 cm, respectively. DEM data were processed in Matlab and ArcGIS.

Geospatial critical coastal infrastructure data were created by students at the University of Rhode Island following trained to use the standard operating procedures developed specifically for the project and applied to available satellite imagery. Publicly available geospatial point data were used as the basis to create polygons for key infrastructure land uses including, airports, energy facilities, marinas, roads, seaports, and water and wastewater treatment. Coordinates were plotted in ESRI ArcGIS and overlaid on aerial imagery to confirm the location of features (0.5m to 1.5m resolution from ESRI World Imagery, last updated January 2018). A polygon dataset of critical infrastructure features were then created using 'heads-up digitizing', a common methodology for spatial data creation used to accurately assesses, monitor and manage a variety of phenomenon (Mas, Puig et al. 2004; Wilson and Lindsey 2005), including to inventory coastal infrastructure (Becker et al. 2010). Additional details on these data sources and methodology are available in the supplementary materials.

2.2. Methods

Extreme Sea Level projections and inundation modelling

Inundation maps of the study area were generated via dynamic simulations using Lisflood-ACC (LFP) (Bates, Horritt et al. 2010, Neal, Schumann et al. 2011) that is part of the Lisflood-FP model (Bates and De Roo 2000). To optimize computational efficiency, the coastline was divided into coastal segments, each with a length of 10 km along the coast and extending up to 50 km inland depending on island size. Simulations took place for each segment; neighboring segments overlapped along 5 km of coastline to ensure generation of seamless inundation maps. The simulations took place at the resolution of each DEM (i.e. 10 m for the NOAA LIDAR dataset, and 30 m for SRTM and CoastalDEM. Further details on the inundation modelling methodology can be found in Vousdoukas et. al (Vousdoukas, Voukouvalas et al. 2016).

Inundation simulations were forced by extreme sea levels (*ESLs*) which consider the combined effect of sea level rise (SLR), the astronomical tide (η_{tide}) and the episodic coastal water level rise (η_{CE}) due to storm surges and wave set up. The projections are available every 10 years for Representative Concentration Pathways (RCPs) 4.5 and 8.5 (Vousdoukas, Mentaschi et al. 2018). Other studies suggest little change to SLR regardless of changes to RCP until the later part of the 20th century (Hu and Bates 2018) due to differences in inertia between atmosphere and ocean temperatures (Meehl, Washington et al. 2005, Schaeffer, Hare et al. 2012). In this analysis, we consider the 100-year storm event in the year 2050 under RCP8.5, to compare sensitivity of the flood model predictions to the DEMs, a set of models was also run for a baseline 100-year event in 2000 (Table 3). More detail of the ESL component can be found in supplemental materials.

<u>Inundation in the coastal zone, DEM validation</u>

The impact of the digital elevation models on flooding were conducted in two steps: 1) a large scale analyses of the coastal zone of the entire USVI Territory comparing CoastalDEM, SRTM and LIDAR, 2) individual coastal infrastructure facilities using the same three datasets.

Storm model output raster files were imported into ArcGIS (10.5.1) and converted to NAD 83 (NSRS2007). Differences between SRTM DEMs and Coastal LIDAR for the entire territory were assessed for $0< x \leq 10$ m elevation using the global parameter Root Mean Square Error (RMSE). Although errors in elevation data may be spatially variable and not well represented by RMSE particularly in areas with large variations in elevation, it is a common parameter used for assessing dispersion.

Indices developed for assessment of fluvial flood models (Bates and De Roo 2000, Alfieri, Salamon et al. 2014, Vousdoukas, Voukouvalas et al. 2016) and applied to coastal flood hazards in a previous study (Vousdoukas, Voukouvalas et al. 2016) were used to calculate ratios of hit (percentage of coastal area correctly predicted by each global model vs. LIDAR), miss (percentage of area missed by the global models vs. LIDAR) and false (percentage of area falsely predicted by the global models compared with L-DEM).

Text Box 1. Hit/Miss/False Ratios

Hit = total coastal area correctly predicted by each DEM model vs. L-DEM:

$$H = \frac{\mathrm{Fm}\cap\mathrm{Fo}}{\mathrm{Fo}} \text{ x } 100$$

where $Fm\cap Fo$ *is the intersection of* Fo *(flooded area predicted by the model L-DEM) and* Fm *(flooded area predicted by the model SRTM, CC-SRTM),*

Miss = total area missed by the predicted model vs. L-DEM:

$$F = \frac{\mathrm{Fm}-\mathrm{Fo}}{\mathrm{Fo}} \text{ x } 100$$

where , $Fm - Fo$ *represents the area under predicted by the SRTM, CC-SRTM models*

False = false alarm or areas overpredicted by the SRTM vs. L-DEM:

$$F = \frac{\mathrm{Fm}/\mathrm{Fo}}{\mathrm{Fo}} \text{ x } 100$$

where the ratio F, Fm/Fo *represents the area over predicted by the SRTM, CC-SRTM models.*

Evaluation of critical coastal infrastructure

To assess variations between the DEMs in predicting flooding of specific coastal features, water heights from the storm model outputs were overlain on elevation and critical coastal infrastructure polygon data in ArcGIS. Connected components analysis was used to ensure all flooded pixels are hydraulically connected to the ocean. Infrastructure data included features common to all types (e.g., buildings), and some unique to functional groups (e.g., clarifier tanks for wastewater treatment). Exposure to parcels and parking lots were calculated as the sum of the inundated portion of total area. For building footprints, if >50% of the area of the footprint was inundated, the area of the entire building footprint were assumed to be exposed. For smaller features (e.g., cranes, tanks, clarifiers, power generating structures and transformers), inundation of any portion of the footprint resulted in the entire area of the feature to be assumed flooded. Finally, in areas where the storm model indicated flooding along portions of access roads within

1 km from the coast, access to the facility was considered impaired and the road tallied as flooded (Tables 1,2).

4. Results

4.1 DEM comparisons

Vertical errors in SRTM and its derived products vary considerably across regions, due to striping and other factors. In St. John and St. Thomas, we found that CoastalDEM contains vertical RMSE of 4.6m, and in St. Croix, 2.6m. SRTM's vertical RMSE approach 5.6m and 4.2m in the same respective areas. The large scale geographic agreement assessment (Figure 1, Table 4) show CoastalDEM model outperformed SRTM-DEM, but both global models underrepresented flood extent. Overall, Coastal-DEM predicted total area over SRTM-DEM at almost 4 times the hit rate (total predicted flood area Coastal DEM ~1100 ha vs. SRTM ~300 ha), although it still only covered 1/5 of the total area predicted flooded by LIDAR. For areas missed by the models as flooded, CoastalDEM outperformed SRTM (~15% increase in overall agreement) with a slightly higher rate of false positives (~3%).

4.2 Coastal transport and utility infrastructure flood exposure

A total of 263 features (e.g., parcels, building footprints, cranes etc.) and 31 roads were evaluated for transport related infrastructure (Tables 1,2), and 110 features (e.g., parcels, clarifiers, transformers) and 15 roads for utilities (Table 3). A large portion of features (building footprints, tanks, parking lots) of cruise/passenger terminals and marina infrastructure, and 25/32 primary access roads for these facilities were flooded. Utilities related infrastructure tended to be located farther inland than transport infrastructure and fared better overall.

4.2.1 Airport flood exposure

Both CoastalDEM and SRTM underestimated flooding at the two primary coastal airports. Using LIDAR elevation data the model identified Cyril E. King (C.E.K.) as potentially more exposed to flooding than Henry E. Rohlson (H.E.R.) (Table 1). All three DEM models indicated runway flooding (LIDAR 6.2 ha, CoastalDEM 4.8 ha, SRTM 1.8 ha) and both taxiways and runways showed flooding for all three elevation models at Cyril King Airport, LIDAR (47%, 59% total area), CoastalDEM (36, 29%) SRTM (10, 14%). CoastalDEM and SRTM correctly predicted nine of fourteen total features as not flooded, however, the area flooded was in agreement in the Western segment of the runway but falsely predicted on the Eastern end by both SRTM based models (Figure 2).

For two features (storage tanks and parking) CoastalDEM and SRTM performed poorly, missing inundation of parking lots and falsely indicating flooding of tanks located ~40 m from the shore, suggesting this overprediction of SRTM or under representation of elevation may have resulted from differences in resolution (LIDAR accurately depicted a steep rise in elevation immediately at the shoreline not indicated on SRTM based DEMs). At H.E.R. (St. Croix) there was only a small amount of inundation to the airport parcel with the exception of parking and the primary access road (Table 1).

4.2.2 Seaports flood exposure

Cargo-Industrial Facilities, Passenger and Ferry Terminals

Results for seaport features are mixed (Table 2, Figure 3). Overall, industrial ports and cargo terminals were less exposed to inundation than cruise and passenger terminals. Based on LIDAR, two industrial terminals (Crown Bay Cargo and Gordon A. Finch Industrial) were completely flooded, and another (Theovald Eric Moorehead cargo terminal) was 90% flooded. These three features account for only 16% of the total cargo industrial feature class area but the majority of flooding. CoastalDEM was within 18% of LIDAR for percent area flooded while SRTM performed poorly.

Cruise and passenger terminal estimates show complete inundation (99% parcel area, 100% of buildings, parking and all primary road access) for the LIDAR model (Table 2). Again, CoastalDEM performed better than SRTM capturing >60% of the flooding of buildings vs. SRTM <30%. Although there is a significant improvement over SRTM, total inundated area is considerably smaller with penetration by LIDAR into areas surrounding terminals (Figure 3).

Marinas

Thirteen marinas (~27 ha over the three USVI, ~2 ha each) were identified, size varied from small facilities (~600 m^2) with several docks, to 7+ ha within a housing complex. In total, 91% of marina parcels, 93% of parking areas and 75 of 85 buildings were flooded with the LIDAR, including a large portion of boat storage areas identified from the aerial photos. CoastalDEM again underestimated flooding (parcel area 21%), but outperformed SRTM (3%) by a wide margin, accounting for 40% of the number of inundated buildings (30/75) vs. 4% SRTM (3/75) (Table 2).

4.2.3 Coastal Utilities Infrastructure

Coastal utility infrastructure estimates (Figure 4, Table 3) show CoastalDEM model underestimated exposure by > 50% and SRTM nearly a complete miss. Clarifiers at wastewater treatment plants were between 20, 35 and 42% flooded (SRTM, CoastalDEM, LIDAR). From the aerial photos used to create the data, many of these appeared to be open topped short stature structures for which over wash could lead to contamination of surrounding areas. Many facilities in this class are located inland of transport infrastructure, and a combination of vertical error and lower resolution SRTM based data may have overrepresented subtle changes in topography that led to less flooding as topography rises away from the coast.

5. Discussion

Using readily available data to efficiently identify storm surge exposure over a wide geographic area, this study presents a methodology that bridges a gap between large-scale global or national studies and single-facility case assessments for critical coastal infrastructure. Applying the methodology to the USVI using LIDAR elevation data we found 51% of coastal transportation and utilities infrastructure could be exposed to coastal flooding in the coming decades. The same assessment method using CoastalDEM identified 27% of those facilities exposed to coastal flooding, and SRTM matched only 6%. Although the important role topographic data quality and hydraulic model selection play in inundation map accuracy is well established, to our knowledge, this is the first study comparing variations in coastal flood exposure assessment outcomes for coastal infrastructure based on DEMs.

There are two primary components that influence exposure estimates, storm model, and digital elevation model, and the impact that each of these have on outcomes can be substantial. Barnard et al. (Barnard, Erikson et al. 2019) found a static storm model to underestimate the total land area flooded by up to 77% compared with a dynamic model. A difference of this magnitude in the present study could bring into play many coastal assets that may not be assessed as exposed using SLR in a static model. In the present study, we chose the DEM uncertainty (RMSE 5-6 vs. GDEM >10) (Gesch 2018). Although there is a demonstrated positive bias in SRTM data (Carabajal and Harding, 2006; Gesch et al., 2016 (Kulp and Strauss 2016, Kulp and Strauss 2018)) and a global dispersion parameter such as RMSE does not capture error from spatially varying factors (Erdogan 2010, Schmidt, Hadley et al. 2011, Zandbergen 2011), we acknowledge this limitation and note infrastructure in this study are sited at or very near sea level and DEM data were compared for a narrow band of coast (0 – 10 m elevation) reflecting RMSE as an appropriate reflection of error for dataset comparisons.

In digital elevation data, vertical accuracy and horizontal resolution have substantive impacts on outcomes (Kenward, Lettenmaier et al. 2000, Bales and Wagner 2009, Gesch 2009, Vaze, Teng et al. 2010, Gesch 2013, Leon, Heuvelink et al. 2014) (Kenward, Lettenmaier et al. 2000, Vaze, Teng et al. 2010) but poor quality data are often used because of a lack of alternative high quality sources that are limited to economically developed areas. Errors in DEMs constitute uncertainty and although incorporating error and uncertainty of DEMs into coastal flood models can reduce the uncertainty of modeled impacts (Gesch, 2009; 2013; Gesch, Gutierrez, and Gill, 2009; Hare, Eakins, and Amante, 2011; Leon, Heuvelink, and Phinn, 2014; (Leon, Heuvelink et al. 2014)) and methods exist to facilitate this (Gesch 2009, Gesch 2013), the algorithms required to calculate and/or map uncertainty and error are challenging to implement and interpret.

In the present study, the inundated area predicted by the storm model was substantially larger using higher-resolution 10 m LIDAR than the global DEMs. This is likely caused by SRTM and CoastalDEM over estimating elevation (RMSE of up to 5.6 for 4-5 level surge). While the vertical errors distorted the model estimates, findings also suggest that larger grid cells failed to capture changes in topography at smaller scales leading to less inundation in areas where elevation changes are smaller than captured in the lower-resolution data, adding to uncertainty in the estimates. This was particularly relevant for small features (e.g., individual buildings) and areas of coast with narrow inlets (e.g., less than ~ 60 m width); the global models tended to miss these features represented in the LIDAR model.

To provide actionable information, we chose a ~30 year time window (2050) for the SLR/storm model, and therefore posit that although the higher end of greenhouse gas emissions trajectory (RCP 8.5) is used in the model, the short time window leads to the results being conservative in nature. To test this assumption and address concerns that RCP 8.5 may over-represent future emissions with possible changes coming in efficiency, abatement technology and or climate policy, we followed identical protocols to analyze RCP of 4.5 (equivalent to a small reduction in emissions from the current trajectory) and found little difference in flood extents between the two pathways. This is consistent with recent projections that suggest little discernable difference between the two scenarios for the first half of the century (Hu and Bates 2018) due to momentum within the climate system. We believe this confirms the conservative nature of the estimates based on LIDAR DEMs for flooding, but what about SRTM based estimates? We acknowledge a short time window biases results against SRTM in light of vertical error equal to or greater than modeled storm surge, but one aim of the present work is assessment of the feasibility of CoastalDEM to efficiently identify facilities in need of in-depth analyses on a regional level. We believe this objective has been fulfilled and that those facilities identified as exposed by the CoastalDEM are truly facilities in most need of attention.

Finally, past estimates using ASTER GDEM of the Caribbean coastal population, suggest that 14 million persons already live below 3 meters elevation and 22 million live below 6 meters ((Lam, et al. 2009). Critical coastal infrastructure, populations and their associated livelihoods are at risk from a combination of SLR, high tides and storm surges of the magnitudes presented in this study. As recent storms in the region have demonstrated, these coastal hazards have a wide range of impacts on the region and pose significant risk to sustainable development (Moore, Elliott et al. 2016, Cashman and Nagdee 2017) and major economic sectors dependent on coastal infrastructure (e.g. tourism, agriculture and international commerce) (Simpson 2010). The Caribbean has been referred to as one of the most natural-disaster prone regions worldwide (Nurse, R.F. McLean et al. 2014, Borurff and Cutter 2018, Monioudi In Press) and we have presented and validated a method applicable at a regional scale for assessment of critical coastal infrastructure exposure.

The method developed in the current study determines exposure based on elevation, location and modeled storm and SLR. The method is targeted to identify and or rank facilities for prioritizing further study over larger scales, and although it identifies exposure for specific features such as buildings, it is not meant to be a method to determine specific risk of flooding for individual facilities. It is limited in this aspect as it does not take into account levees and other coastal protection features if they are not identified in satellite imagery or the digital elevation models.

6. Conclusion

To our knowledge, this is the first study to assess exposure of critical coastal infrastructure assets that incorporates a method for national or regional scales with specificity to rank facilities by exposure. Although SRTM based DEMs introduce significant error into the assessment, that error does not preclude ranking facilities to efficiently direct resources for further study to protect critical components of local, national and regional economies from climate-related disasters. All coastal infrastructure is vulnerable to the effects of climate change, but not all is equally so and not all will undergo fortification needed to withstand likely impacts. In providing a model that does not require extensive data processing, this method is accessible to analyze infrastructure over broad spatial scales.

Society relies heavily on critical coastal infrastructure for the movement of people, goods and services, meaning these facilities are amongst the most important assets a changing climate will impact. Recent hurricanes in the Caribbean have caused major disruptions to the continuous and uninterrupted operations of critical coastal infrastructure, challenging economic development. The resources to plan for such large scale exposure have thus far been in short supply, driving the need for cost effective approaches in the development of plans to manage it. There is an urgent need for increased quantity and quality of information on coastal flood risk, but studies should proceed with caution, considering; error associated with the underlying elevation data, error in the approaches used in assessments, and the potential setbacks to progress in climate mitigation when these factors are not carefully considered. This method is not targeted directly at providing informed policy decisions, but as a valuable component towards efficiently achieving that aim.

Supplemental Materials

Creation of Coastal infrastructure data

Polygon parcel outlines of infrastructure required the analyst to follow specific guidance developed as part of the project to ensure replicability of the process. Sub-features of parcels (e.g., tanks, buildings) were digitized and organized in a relational database based on sub-feature type. Imagery used for digitizing included 15m TerraColor imagery at small and mid-scales (~1:591M down to ~1:72k) and 2.5m SPOT Imagery (~1:288k to ~1:72k) for the world. In the USVI, 0.5 meter or better resolution were available. ESRI World Imagery utilizes an image layer stack that displays different images depending on the viewing scale. The images available in the stack vary based on location. ESRI World Imagery provides two sets of images with resolution suitable for heads-up digitizing. The first, a set of images viewable between 1:200,000 – 1:4,000 with 0.5 m resolution, captured in 2016; the second, a set viewable from the scale of 1:3,000 with 0.3 m resolution, captured in 2010. To capture recent features in the landscape, the 2016 set was used except in cases cloud cover obstructed ground features, the 2010 imagery from ESRI World Imagery with equal or better resolution was used. Features digitized are listed in tables 1 and 2.

Constraints to this approach stem from accuracy/resolution of the primary source information. Satellite imagery is not necessarily synoptic, is collected at different times and under different atmospheric conditions. Error in digitizing due to sensor angle, cloud cover and image acquisition date (new construction or demolition). Researchers utilized the most current images free from cloud cover when creating the infrastructure inventory. Furthermore, sensor angle potentially caused small variations in the true ground location of assets versus the digitized projected data. Nevertheless, small (horizontal) shifts or offsets of ground features captured in this manner are unavoidable in large scale studies based on satellite imagery.

Sources for creation of infrastructure inventory

Infrastructure Type	Data Source	URL	Source Type	Date Accessed
Seaports	World Port Source	http://www.worldportsource.com/	Global dataset	February 2018
Airports	Open Flights	https://openflights.org/	Global dataset	February 2018
Energy Facilities	U.S. Virgin Islands Water and Power Authority	http://www.viwapa.vi/Home.aspx	Local government	March 2018
Water Treatment Facilities	U.S. Virgin Islands Water and Power Authority	http://www.viwapa.vi/Home.aspx	Local government	March 2018
Wastewater Treatment Facilities	U.S. Virgin Islands Waste Management Authority	http://www.viwma.org/	Local government	March 2018
Marinas	VInow	https://www.vinow.com/	Travel agency	May 2018
Roads	U.S. Census	https://www.census.gov/geo/maps-data/data/tiger-line.html	National dataset	June 2018

Extreme Sea Level (ESL) component of the Storm Model

Hindcasts of storm surge levels (*SSLs*) and waves (1980-2015) were obtained through simulations forced by ERA-INTERIM atmospheric conditions. One-percent annual probability storm surge levels were simulated using a flexible mesh setup of the DFLOW FM model (Muis, Verlaan et al. 2016). Offshore significant wave heights (*H*s), periods (*T*) and directions along the USVI coast were estimated using the WAVEWATCH III model (Tolman 2009).

Sea level rise (*SLR*) projections were taken from (Jevrejeva, Jackson et al. 2016) whereas the DFLOW FM model was used to assess *SLR*-induced changes in tidal elevations (Vousdoukas, Mentaschi et al. 2017). Changes in waves and storm surges were assessed through another series of simulations using the WAVEWATCH III and DFLOW-FM models, respectively. The simulations were forced by a six-member GCM ensemble from the CMIP5 database (Vousdoukas, Mentaschi et al. 2018). Wave incidence was obtained by combining the mean wave direction from the model with the mean shoreline orientation along 500 m long coastline sections. For the estimation of the nearshore wave conditions, Snell's law was applied to assess transformation due to shoaling, assuming a seabed slope of 1.5 % (a widely used approximation). Finally, wave set up (η_s) was estimated using the generic approximation (0.2 x Hs) of CEM (CEM 2002) and combined with *SSLs* to generate the η_{CE} components of the *ESLs*.

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References

Alfieri, L., P. Salamon, A. Bianchi, J. Neal, P. Bates and L. Feyen (2014). "Advances in pan-European flood hazard mapping." Hydrological Processes **28**(13): 4067-4077.

Bales, J. D. and C. R. Wagner (2009). "Sources of uncertainty in flood inundation maps." Journal of Flood Risk Management **2**(2): 139-147.

Barnard, P. L., L. H. Erikson, A. C. Foxgrover, J. A. F. Hart, P. Limber, A. C. O'Neill, M. van Ormondt, S. Vitousek, N. Wood, M. K. Hayden and J. M. Jones (2019). "Dynamic flood modeling essential to assess the coastal impacts of climate change." Scientific Reports **9**(1): 4309.

Bates, P. D. and A. P. J. De Roo (2000). "A simple raster-based model for flood inundation simulation." Journal of Hydrology **236**(1-2): 54-77.

Bates, P. D., M. S. Horritt and T. J. Fewtrell (2010). "A simple inertial formulation of the shallow water equations for efficient two-dimensional flood inundation modelling." Journal of Hydrology **387**(1-2): 33-45.

Baugh, C. A., P. D. Bates, G. Schumann and M. A. Trigg (2013). "SRTM vegetation removal and hydrodynamic modeling accuracy." Water Resources Research **49**(9): 5276-5289.

Becek, K. (2014). "Assessing Global Digital Elevation Models Using the Runway Method: The Advanced Spaceborne Thermal Emission and Reflection Radiometer Versus the Shuttle Radar Topography Mission Case." Ieee Transactions on Geoscience and Remote Sensing **52**(8): 4823-4831.

Borurff, B. and S. L. Cutter (2018). "The Environmental Vulnerability of Caribbean Island Nations." Geographical Review **97**(1): 24-45.

Cashman, A. and M. R. Nagdee (2017). "Impacts of Climate Change on Settlements and Infrastructure in the Coastal and Marine Environments of Caribbean Small Island Developing States (SIDS)." CARIBBEAN MARINE CLIMATE CHANGE REPORT CARD: SCIENCE REVIEW: 157-173.

Cashman, A., Nagdee, M.R. (2017). "Impact of Climate Change on Settlements and Infrastructure in the Coastal and Marine Environments of Caribbean Small Island Developing States (SIDS)." Science Review: 155-173.

CEM (2002). "Coastal Engineering Manual." U.S. Army Corps of Engineers, Washington, DC.

Chhetri, P., J. Corcoran, V. Gekara, C. Maddox and D. McEvoy (2015). "Seaport resilience to climate change: mapping vulnerability to sea-level rise." Journal of Spatial Science **60**(1): 65-78.

Duncan McIntosh, R. and A. Becker (2017). Seaport Climate Vulnerability Assessment at the Multi-port Scale: A Review of Approaches, Dordrecht, Springer Netherlands.

Erdogan, S. (2010). "Modelling the spatial distribution of DEM error with geographically weighted regression: An experimental study." Computers & Geosciences **36**(1): 34-43.

Falorni, G., V. Teles, E. R. Vivoni, R. L. Bras and K. S. Amaratunga (2005). "Analysis and characterization of the vertical accuracy of digital elevation models from the Shuttle Radar Topography Mission." Journal of Geophysical Research-Earth Surface **110**(F2).

Gesch, D. B. (2009). "Analysis of Lidar Elevation Data for Improved Identification and Delineation of Lands Vulnerable to Sea-Level Rise." Journal of Coastal Research **25**(6): 49-58.

Gesch, D. B. (2013). "Consideration of Vertical Uncertainty in Elevation-Based Sea-Level Rise Assessments: Mobile Bay, Alabama Case Study." Journal of Coastal Research: 197-210.

Gesch, D. B. (2018). "Best Practices for Elevation-Based Assessments of Sea-Level Rise and Coastal Flooding Exposure." Frontiers in Earth Science **6**.

Hall, O., G. Falorni and R. L. Bras (2005). "Characterization and quantification of data voids in the shuttle radar iopography mission data." Ieee Geoscience and Remote Sensing Letters **2**(2): 177-181.

Hinkel, J., D. Lincke, A. T. Vafeidis, M. Perrette, R. J. Nicholls, R. S. J. Tol, B. Marzeion, X. Fettweis, C. Ionescu and A. Levermann (2014). "Coastal flood damage and adaptation costs under 21st century sea-level rise." Proceedings of the National Academy of Sciences of the United States of America **111**(9): 3292-3297.

Hu, A. and S. C. Bates (2018). "Internal climate variability and projected future regional steric and dynamic sea level rise." Nature Communications **9**.

Jarihani, A. A., J. N. Callow, T. R. McVicar, T. G. Van Niel and J. R. Larsen (2015). "Satellite-derived Digital Elevation Model (DEM) selection, preparation and correction for hydrodynamic modelling in large, low-gradient and data-sparse catchments." Journal of Hydrology **524**: 489-506.

Jevrejeva, S., L. P. Jackson, E. M. Riva, A. Grinsted and J. C. Moore (2016). "Coastal sea level rise with warming above 2 degrees C." Proceedings of the National Academy of Sciences of the United States of America **113**(47): 13342-13347.

Kantamaneni, K. (2016). "Coastal infrastructure vulnerability: an integrated assessment model." Natural Hazards **84**(1): 139-154.

Kenward, T., D. P. Lettenmaier, E. F. Wood and E. Fielding (2000). "Effects of digital elevation model accuracy on hydrologic predictions." Remote Sensing of Environment **74**(3): 432-444.

Kulp, S. and B. H. Strauss (2016). "Global DEM Errors Underpredict Coastal Vulnerability to Sea Level Rise and Flooding." Frontiers in Earth Science **4**.

Kulp, S. A. and B. H. Strauss (2018). "CoastalDEM: A global coastal digital elevation model improved from SRTM using a neural network." Remote Sensing of Environment **206**: 231-239.

Kumar, L. and S. Taylor (2015). "Exposure of coastal built assets in the South Pacific to climate risks." Nature Climate Change **5**: 992.

LaLonde, T., A. Shortridge and J. Messina (2010). "The Influence of Land Cover on Shuttle Radar Topography Mission (SRTM) Elevations in Low-relief Areas." Transactions in Gis **14**(4): 461-479.

Lam, N. S. N., H. Arenas, P. L. Brito and K. B. Liu (2014). "Assessment of vulnerability and adaptive capacity to coastal hazards in the Caribbean Region." Journal of Coastal Research: 473-478.

Leon, J. X., G. B. M. Heuvelink and S. R. Phinn (2014). "Incorporating DEM Uncertainty in Coastal Inundation Mapping." Plos One **9**(9).

Li, J. and D. W. S. Wong (2010). "Effects of DEM sources on hydrologic applications." Computers Environment and Urban Systems **34**(3): 251-261.

Lichter, M. and D. Felsenstein (2012). "Assessing the costs of sea-level rise and extreme flooding at the local level: A GIS-based approach." Ocean & Coastal Management **59**: 47-62.

McGranahan, G., D. Balk and B. Anderson (2007). "The rising tide: assessing the risks of climate change and human settlements in low elevation coastal zones." Environment and Urbanization **19**(1): 17-37.

Meehl, G. A., W. M. Washington, W. D. Collins, J. M. Arblaster, A. X. Hu, L. E. Buja, W. G. Strand and H. Y. Teng (2005). "How much more global warming and sea level rise?" Science **307**(5716): 1769-1772.

Monioudi, I., Asariotis, R., Becker, A., Dowding-Gooden, D., Esteban, M., Mentaschi, L., Nikolaou, A., Nurse, L., Phillips, W., Smith, D., Satoh, M., Snow-Bhat, C., Trotz, U., Velegrakis, A., Voukouvalas, E., Vousdoukas, M., Witkop, R. (In Press). "Climate change impacts on critical international transportation assets of Caribbean Small Island Developing States (SIDS): The case of Jamaica and Saint Lucia. ." Regional Environmental Change.

Monioudi, I. N., R. Asariotis, A. Becker, C. Bhat, D. Dowding-Gooden, M. Esteban, L. Feyen, L. Mentaschi, A. Nikolaou, L. Nurse, W. Phillips, D. A. Y. Smith, M. Satoh, U. O. Trotz, A. F. Velegrakis, E. Voukouvalas, M. I. Vousdoukas and R. Witkop (2018). "Climate change impacts on critical international transportation assets of Caribbean Small Island Developing States (SIDS): the case of Jamaica and Saint Lucia." Regional Environmental Change **18**(8): 2211-2225.

Moore, W., W. Elliott and T. Lorde (2016). "Climate change, Atlantic storm activity and the regional socio-economic impacts on the Caribbean." Environment, Development and Sustainability **19**(2): 707-726.

Muis, S., M. Verlaan, H. C. Winsemius, J. C. J. H. Aerts and P. J. Ward (2016). "A global reanalysis of storm surges and extreme sea levels." Nature Communications **7**.

Neal, J., G. Schumann, T. Fewtrell, M. Budimir, P. Bates and D. Mason (2011). "Evaluating a new LISFLOOD-FP formulation with data from the summer 2007 floods in Tewkesbury, UK." Journal of Flood Risk Management **4**(2): 88-95.

Neumann, B., A. T. Vafeidis, J. Zimmermann and R. J. Nicholls (2015). "Future Coastal Population Growth and Exposure to Sea-Level Rise and Coastal Flooding - A Global Assessment." Plos One **10**(3).

Nurse, L. A., R.F. McLean, J. Agard, L.P. Briguglio, V. Duvat-Magnan, N. Pelesikoti, E. Tompkins and A.Webb (2014). Small Islands. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. V. R. Barros, C.B. Field, D.J. Dokken et al. Cambridge, UK and New York, NY, Cambrdige University Press**:** 1613-1654.

Office for Coastal Management "2013 NOAA Topographic Lidar: US Virgin Islands Digital Elevation Models (DEMs) from 2013-11-09 to 2013-12-10 NOAA National Centers for Environmental Information."

Rasmussen, D. J., K. Bittermann, M. K. Buchanan, S. Kulp, B. H. Strauss, R. E. Kopp and M. Oppenheimer (2018). "Extreme sea level implications of 1.5 degrees C, 2.0 degrees C, and 2.5 degrees C temperature stabilization targets in the 21st and 22nd centuries." Environmental Research Letters **13**(3).

Sanders, B. F. (2007). "Evaluation of on-line DEMs for flood inundation modeling." Advances in Water Resources **30**(8): 1831-1843.

Schaeffer, M., W. Hare, S. Rahmstorf and M. Vermeer (2012). "Long-term sea-level rise implied by 1.5 degrees C and 2 degrees C warming levels." Nature Climate Change **2**(12): 867-870.

Schmidt, K. A., B. C. Hadley and N. Wijekoon (2011). "Vertical Accuracy and Use of Topographic LIDAR Data in Coastal Marshes." Journal of Coastal Research **27**(6a): 116-132.

Shortridge, A. and J. Messina (2011). "Spatial structure and landscape associations of SRTM error." Remote Sensing of Environment **115**(6): 1576-1587.

Simpson, M. C. (2010). Quantification and Magnitude of Losses and Damages Resulting from the Impacts of Climate Change: Modelling the Transformational Impacts and Costs of Sea Level Rise in the Caribbean (Key Points andSummary for Policy Makers Document). Quantification and Magnitudeof Losses and Damages Resulting from the Impacts of Climate Change: Modelling the Transformational Impacts and Costs of Sea Level Rise in the Caribbean (Key Points andSummary for Policy Makers Document), United Nations Development Programme (UNDP).

Smith, K. (2011). "We are seven billion." Nature Climate Change **1**(7): 331-335.

Taramelli, A., E. Valentini and S. Sterlacchini (2015). "A GIS-based approach for hurricane hazard and vulnerability assessment in the Cayman Islands." Ocean & Coastal Management **108**: 116-130.

Tolman, H. L. (2009). "User manual and system documentation of WAVEWATCH-III version 3.14."

USGCRP (United States Global Change Research Program) (2017). Climate Science Special Report: Fourth National Climate Assessment, Volume I. D. J. Wuebbles, D. W. Fahey, K. A. Hibbard et al. Washington, DC, USA, U.S. Global Change Research Program**:** 470.

van de Sande, B., J. Lansen and C. Hoyng (2012). "Sensitivity of Coastal Flood Risk Assessments to Digital Elevation Models." Water **4**(3): 568-579.

Vaze, J., J. Teng and G. Spencer (2010). "Impact of DEM accuracy and resolution on topographic indices." Environmental Modelling & Software **25**(10): 1086-1098.

Vousdoukas, M. I., D. Bouziotas, A. Giardino, L. M. Bouwer, L. Mentaschi, E. Voukouvalas and L. Feyen (2018). "Understanding epistemic uncertainty in large-scale coastal flood risk assessment for present and future climates." Natural Hazards and Earth System Sciences **18**(8): 2127-2142.

Vousdoukas, M. I., L. Mentaschi, E. Voukouvalas, M. Verlaan and L. Feyen (2017). "Extreme sea levels on the rise along Europe's coasts." Earths Future **5**(3): 304-323.

Vousdoukas, M. I., L. Mentaschi, E. Voukouvalas, M. Verlaan, S. Jevrejeva, L. P. Jackson and L. Feyen (2018). "Global probabilistic projections of extreme sea levels show intensification of coastal flood hazard." Nature Communications **9**.

Vousdoukas, M. I., L. Mentaschi, E. Voukouvalas, M. Verlaan, S. Jevrejeva, L. P. Jackson and L. Feyen (2018). "Global probabilistic projections of extreme sea levels show intensification of coastal flood hazard." Nature Communications **9**(1): 2360.

Vousdoukas, M. I., E. Voukouvalas, L. Mentaschi, F. Dottori, A. Giardino, D. Bouziotas, A. Bianchi, P. Salamon and L. Feyen (2016). "Developments in large-scale coastal flood hazard mapping." Natural Hazards and Earth System Sciences **16**(8): 1841-1853.

Wang, W. C., X. X. Yang and T. D. Yao (2012). "Evaluation of ASTER GDEM and SRTM and their suitability in hydraulic modelling of a glacial lake outburst flood in southeast Tibet." Hydrological Processes **26**(2): 213-225.

Yamazaki, D., D. Ikeshima, R. Tawatari, T. Yamaguchi, F. O'Loughlin, J. C. Neal, C. C. Sampson, S. Kanae and P. D. Bates (2017). "A high-accuracy map of global terrain elevations." Geophysical Research Letters **44**(11): 5844-5853.

Zandbergen, P. A. (2011). "Characterizing the error distribution of lidar elevation data for North Carolina." International Journal of Remote Sensing **32**(2): 409-430.

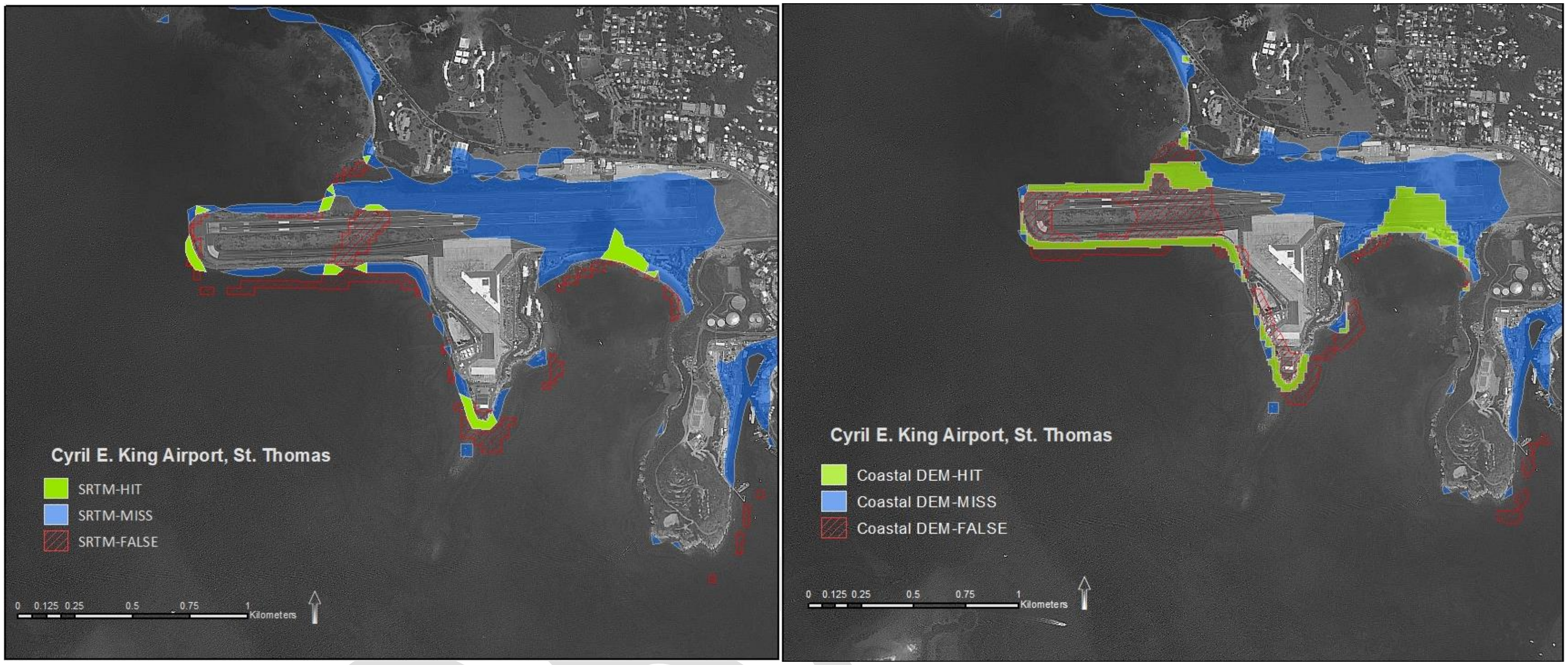

Figure 1

Airport inundation based on extreme sea-level and storm surge model, SRTM and CoastalDEM elevation tested with Hit/Miss/False analyses

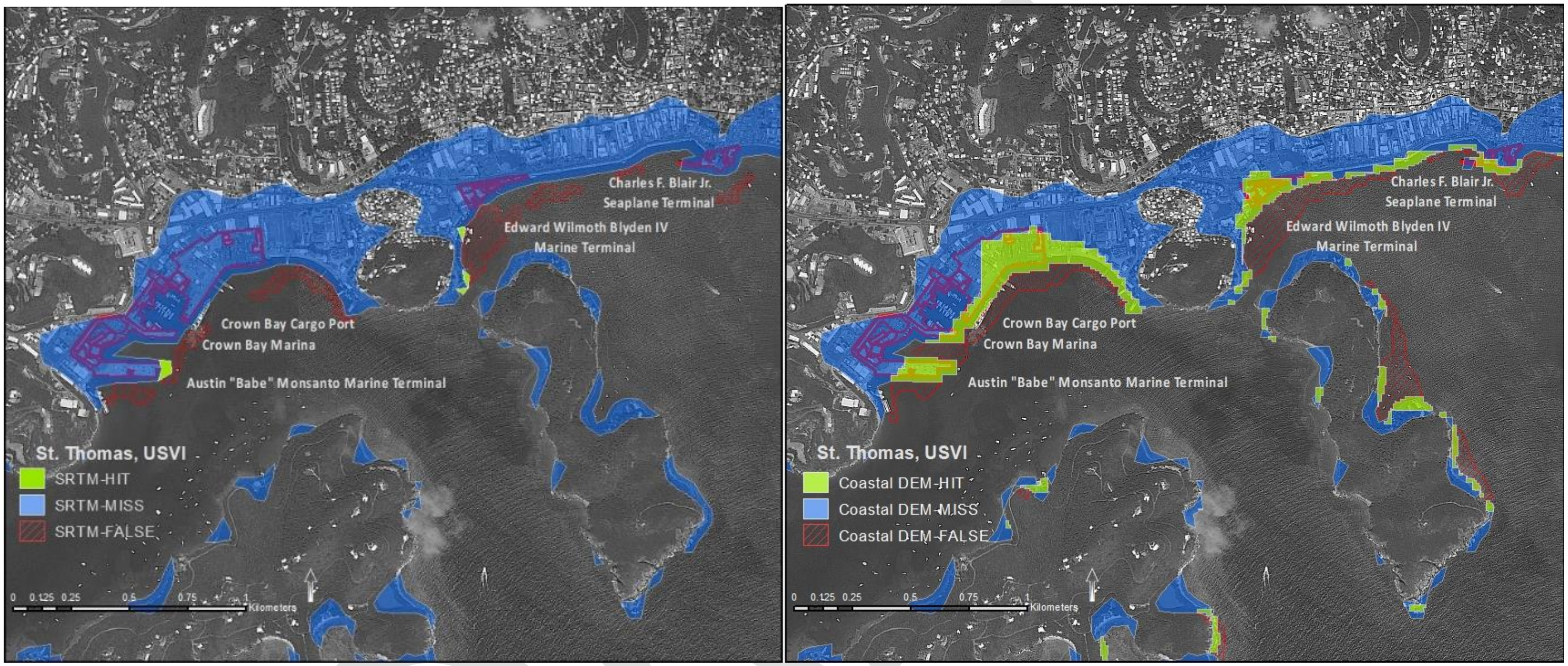

Figure 2

Results of extreme sea-level and storm surge model on transportation infrastructure, LIDAR DEM vs. SRTM and CoastalDEM elevation Hit/Miss/False analyses

Figure 3

Electric power substation on St. John, USVI, extreme sea-level and storm surge model tested with SRTM and CoastalDEM elevation with Hit/Miss/False analyses using LIDAR elevation data

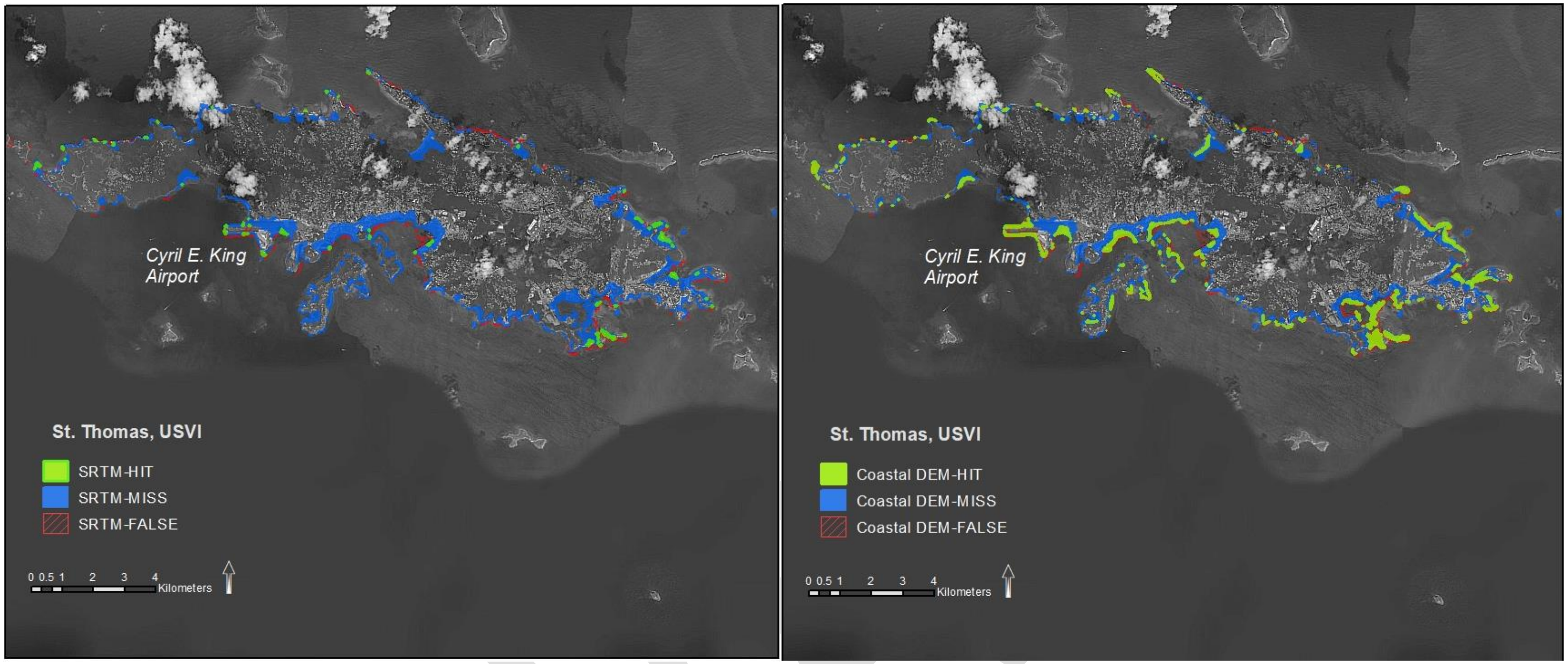

Figure 4

Hit/Miss/False analyses of SRTM, CoastalDEM versus Lidar, results from LISFLOOD model of extreme sea level and storm model. Blue area represents underestimation of flood extent using SRTM based elevation

Table 1. Airports

Airports (C.K. | H.R.)[a]	Total Footprint (m^2)		% Area Flooded (# Structures Flooded)					
			Lidar		CoastalDEM		SRTM	
	C.K.	H.R.	C.K.	H.R.	C.K.	H.R.	C.K.	H.R.
Parcels (1 | 1)	1,187,285	2,790,285	34	1	23	0	9	0
Building Footprints (6 | 16)	8,227	17,665	0	0	0	0	0	0
Parking Lots (1 | 1)	25,791	17,350	0	35	0	0	0	0
Tanks[b] (6 | 0)	2,582	--	0	--	70(4)	--	22(1)	--
Runway (1 | 1)	133,591	219,749	47	0	36	0	14	0
Taxiway (2 | 1)	154,273	108,387	59	0	29	0	10	0
Tower[c] (1 | 1)	--	413	--	0	--	0	--	0
Terminal (1 | 1)	22,893	18,620	0	0	0	0	0	0
Road Access			Flooded	Flooded	Flooded	Not Flooded	Flooded	Not Flooded

a.Cyril E. King, Henry E. Rohlson, b. includes individual tanks and footprints with multiple small tanks, c. tower at C.K. is part of terminal building

Table 2. Seaports\Cruise and Passenger Terminals\Marinas

Seaports - Industrial Facilities and Cargo Terminals[a]		% Area Flooded (# Structures Flooded)		
	Total Footprint (m^2)	Lidar	CoastalDEM	SRTM
Parcels (6)	738,398	17	14	2
Building Footprints (37)	276,485	3 (6)	2 (3)	0
Cranes (2)	525	100 (2)	100 (2)	0
Parking Lots (3)	3,292	100 (3)	100 (3)	0
Tanks[b] (14)	14,640	26 (5)	8 (2)	0
Road Access		Flooded-3, Not Flooded-3	Flooded-2, Not Flooded-4	Flooded - 0
Cruise and Passenger Terminals				
Parcels (10)	190,226	99	32	9
Building Footprints (32)	29,339	100 (32)	85 (21)	22(9)
Parking Lots (9)	27,670	100	50	2
Road Access		Flooded-10, Not Flooded-0	Flooded-6, Not Flooded-4	Flooded - 0
Marinas				
Parcels (13)	267,655	91	21	3
Building footprints (85)	35,889	91 (75)	64 (30)	4(3)
Parking Lots (9)	28,448	93 (9)	7 (2)	1(1)
Road Access		Flooded-9, Not Flooded-4	Flooded-1, Not Flooded-12	Flooded - 0

1. shaded results represent > 50% difference with LIDAR, a. does not include Lime Tree Bay industrial complex, b. includes individual tanks and footprints with multiple small tanks

Table 3. Utilities[1]

Electric[a,b,c]		% Area Flooded (# Structures Flooded)		
	Total Footprint (m^2)	Lidar	CoastalDEM	SRTM
Parcel (8)	313,423	13	4	0
Buildings (21)	10,806	37 (9)	6 (4)	0
Power Generating Structures & Transformers (18)	22,085	53 (6)	2 (4)	0
Tanks (10)	14,862	10 (2)	0	0
Access Roads		Flooded-1 Not Flooded-7	Flooded-1 Not Flooded-7	Flooded - 0
Water Treatment				
Parcels (7)	317,669	17	5	2
Building footprints (27)	13,895	38(7)	8(2)	0
Clarifiers (19)	13,191	42(6)	35(5)	20(1)
Access Roads		Flooded-4 , Not flooded 3	Flooded – 1 , Not flooded 6	Flooded – 0

1. Shaded results represent > 50 % difference, a. includes one Solar facility (Spanish Town), b. does not includes electrical power structures at Lime Tree Bay Industrial Facility, c. Randolph water treatment plant included in Electric and Water Treatment categories

Table 4. DEM Comparisons

Root Mean Square Error and Impact of DEM On Modeled Storm Output vs. Lidar

RMSE (elevation $0 < x \leq 10m$)[a]	SRTM	Coastal-DEM
St. John, St. Thomas	5.6	4.6
St. Croix	4.2	2.6

Hit/Miss/False[b]	**Baseline – Year 2000**		**RCP 8.5 – Year 2050**	
	SRTM	CoastalDEM	SRTM	CoastalDEM
Hit	5	22	6	20
Miss	92	78	93	80
False	2	6	2	5

a. Coastal file between 0-10 m elevation
b. Hit - % total flood area congruent with lidar/Miss - % predicted by lidar but not comparison models/False - % predicted by comparison model but not lidar